Systolic Blood Pressure Estimation from Electrocardiogram and Photo Plethysmogram Signals Using Convolutional Neural Networks

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Abstract

Background: Digital continuous blood pressure (BP) monitoring is increasingly being used in clinical and remote settings. Although it could significantly help clinicians in vital signs monitoring, the analyzing of such amount of BP data is challenging.

Objective: This study is aimed to investigate the feasibility of applying deep convolutional neural network (CNN) to the estimation of the systolic blood pressure (SBP) using electrocardiogram (ECG) and photo plethysmography (PPG) signals.

Method: A total of 62500 ECG and PPG signals, sampled at 125 Hz, with 250 corresponding SBP, sampled at 1 Hz, were selected from Medical Information Mart for Intensive Care (MIMIC-III) Waveform Database. The collected signals from 22 subjects were divided into training (80%) and testing (20%) datasets. A CNN-based model was designed with five convolutional layers, one fully connected layer, and one regression layer to predict the SBP. Two different methods of applying data to the input of the CNN model was evaluated. In the first method, the continuous wavelet transform of the data was used while in the second method, the raw ECG and PPG signals without preprocessing were used as the input dataset.

Results: The results showed a high accuracy of 87.42% for the first method and 90.31% for the second method. Moreover, the mean square errors of 5.43 mmHg and 4.82 mmHg were measured for first and second models, respectively.

Conclusions: Both methods are capable of learning how to extract relevant features from the ECG and PPG signals and estimate SBP within an acceptable error margin set by Association for the Advancement of Medical Instrumentation (AAMI).

Keywords

Continuous blood pressure, Cuff-less blood pressure, Electrocardiogram, Photoplethysmogram, Convolutional neural network

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1. Introduction

Blood pressure (BP) is a vital physiological parameter of the human body that can develop a highly prevalent risk factor worldwide [1]. BP could be varying over time due to physical condition, physiological rhythm, environmental conditions, and so many other factors. Early detection of diseases related to high BP could dramatically decrease disability and mortality rate by maintaining control at the earlier stages of the disease. Continuous BP monitoring is one of the most promising and accurate methods to monitor BP through home-based or clinically measurement [2]. Moreover, there is a high demand for global healthcare toward a wearable sensor and personalized medicine. Thus, the wearable continuous BP devices give the chances of early diagnosis and proper clinical treatments for cardiovascular patients [3].

The most accurate and clinically accepted continuous BP measurement methods mostly include arterial tonometry tension and volume compensation parameters, and pulse wave velocity (PWV) parameters [4]. The arterial tonometry method applicable to radial artery and does not need calibration and accurate for long-time monitoring; however, the utilize sensor could be so sensitive to motion artifacts [5]. Employing volume compensation-based method for BP monitoring devices required a reference pressure setting which makes the measurement complicated. Moreover, the patients will experience considerable pains due to continuous pressure in venous congestion [4]. The relationship between blood pressure and PWV was first theoretically validated by

Moens and Korteweg (M-K) [6]. The PWV method achieved a more straightforward design for BP measuring devices and solved the somberness of patient's comfortability in long-term monitoring.

With recent developments in artificial intelligence as applied to healthcare, the potential in achieving significant improvements and providing real-time, and better personalized medical devices at lower costs is increasing [7]. The researchers have recognized the remarkable potential of artificial intelligence in healthcare to improve the people wellbeing towards cuff-less BP measurement [8-12]. Considering the ability of machine learning to learn the function of the complex system makes it a promising method for BP estimation. A well-trained model can address the latent affecting parameters that cannot be measured in the analytical model. The main idea is to use machine learning to extract surrogate cardiovascular features from time-domain or frequency-domain of physiological signals, then train the data with a machine learning-based model, and finally estimate the BP through the developed model [13].

Deep learning is a subfield of machine learning that has a powerful ability to handle supervised and unsupervised learning, besides solve different type of classification and identification problems. Deep learning has shown promising results in object detection [14], speech recognition [15], and image recognition [16]. This technique also used in biomedical technologies such as risk assessment for hypertension [17,18], and echocardiography images analysis [19,20]. But to the availability of a vast amount of medical data, deep learning is considered as a powerful tool in the mining of medical data collected from monitoring and wearables devices. In general, deep belief networks (DBN), stacked auto encoders (SAE), and CNN are typical structures of deep learning models [21].

In this study, a CNN-based architecture to estimate the SBP from ECG and PPG signals was designed in order to eliminate the engineered feature extraction process. This paper is an extension of work initially presented at the pHealth-2019 conference [22]. We increased the size of the training data, modified the CNN design, and compared the new models with selected studies in the same field.

2. Material and Methods

2.1 Database

The database has been used for this study is Medical Information Mart for Intensive Care (MIMIC-III) Waveform Database Matched Subset [23], which is a subset of the MIMIC-III Waveform Database. This database is included in multiple physiologic waveforms and numeric time series of vital sign measurements. It contains 22,317 waveform records, and 22,247 numeric records collected from 10,282 distinct ICU patients that have been matched and time-aligned with MIMIC-III Clinical Database records.

To evaluate both proposed methods, we chose subjects with available ECG, PPG and SBP signals, and after time synchronization, the related waveforms were extracted to use as training and testing data. The data collected form a total of 22 patients in ICU. Ultimately, after removing the missing and uncompleted data, 62500 ECG and PPG samples, sampled 125 times per second, with 250 corresponding SBP, sampled one time per second were collected for the experiment.

2.2 Convolutional Neural Networks (CNN) Architecture

Deep learning has shown promising results in healthcare applications such as risk assessment for hypertension [17,18], and echocardiography images analysis [19,20]. CNN can be categorized as a class of deep neural network [24], and it is known as the most popular technique in deep learning [25]. Like other deep learning models, CNN is a hierarchical machine learning tool, commonly consists of input and output layers as well as multiple hidden convolutional layers in sequence. Inspired by the success of CNN in the fields of speech analysis and recognition as well as emotion recognition [26-29], the CNN-based architecture has been applied to continuous and cuff-less BP monitoring in this study. One of the significant benefits of such method is the ability of CNNs to perform perception tasks, which allows them to learn the BP relevant features from ECG and PPG signals and skip the complicated feature extraction step.

Although there are a variety of pre-trained CNN networks such as AlexNet, GoogLeNet, and ResNet, we designed a CNN from scratch due to the complexity of the selected training dataset. The software environment used for this research was MATLAB R2020-a with Intel Core i7-6700 GPU.

We developed two methods based on CNN to estimate BP. The first method employs continuous wavelet transform (CWT) of the data while in the second method, the raw ECG and PPG signals are used without preprocessing as the input data.

3.3 The First Method

In this method, the CWT of the selected ECG and PPG dataset was calculated and presented as the input to the proposed CNN for estimating the SBP. The scalogram of the ECG and PPG signals was created using CWT and employed to train and test the proposed CNN model.

2.3.1 ECG and PPG Scalograms using CWT: The CWT is one of the effective techniques that performs time-frequency analysis of the desired signals. This method is suitable for extracting high-frequency components of the signals in a short period. The CWT of a signal $X(t) \in L2(R)$ could be expressed as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int X(t) * (\frac{t-b}{a}) dt \quad (1)$$

where X(t) is the signal in the time domain, '*' operator denotes the complex conjugate and $\psi(t)$ is the mother wavelet scaled by a factor a, a>0, and dilated by a factor b.

The absolute value of the CWT coefficients of a signal can be considered as the scalogram, which is a function of time and frequency. Since the ECG is related to heart activity and PPG is a fusion of the microcirculation system that detects the changes in blood volume, their time-frequency domain parameters are essential in this study. Therefore, CWT is used to produce

Red-Green-Blue (RGB) images from the selected ECG and PPG signals. Each cardiac cycle converted to a scalogram over both time and frequency, which can locate different frequency components of the signals.

The absolute value of CWT was obtained using the analytic Morse wavelet through the Wavelet toolbox of MATLAB with the symmetry parameter (gamma) equal to 3 and the time-bandwidth product equal to 60. Each scalogram was generated in size of 41×250×1- pixel RGB image. In total, 500 scalogram images were generated from time-synchronized ECG and PPG as well as 250 SBP corresponding reading.

A sample of ECG, and PPG and its corresponding scalograms created for this study are illustrated in Figure 1.

2.3.2 The Proposed CNN Architecture and Training Model: The proposed CNN has five convolutional layers (C1 to C5), one fully connected layer, and one regression layer. The ECG and PPG scalograms passed through the proposed network to extract the relevant features. The training data sorted as 41×250×2 array, where 41 is the height and 250 is the width of the pixels in the grey-scaled images, and 2 is numbers of channels (ECG and PPG). The first convolutional layer (C1) has eight kernels of size (3×3×1) with applied at stride setting of 2 pixels. It is followed by batch normalization layer with eight channels to normalize the prediction of the network when training starts. A ReLU layer used to improve the efficiency of the training process and an average pooling layer with a stride of two implied respectively. The second convolutional layer (C2) has 16 kernels of size (3×3×8) which applied to the input with a stride of two pixels. Correspondingly, followed by batch normalization, ReLU, and average pooling layers. The third convolutional layer (C3) has 32 kernels of size (3×3×16) and followed as the previous one. The fourth convolutional layer (C4) has 32 kernels of size (3×3×32), followed by batch normalization, ReLU, and average pooling layers. The last convolutional layer (C5) has 64 kernels of size (3×3×64) and followed by a fully connected layer of one neuron. To reduce the overfitting, a dropout layer that performs regularization with a dropout ratio of 20% is used before fully connected layer. A regression layer is used to estimate the BP from the final fully connected layer in Figure 2.

2.4 The Second Method

In the second method, we used raw ECG and PPG signals without preprocessing as the input data. Although the PPG signals are noisy, and the preprocessing need to be considered, the PPG signals from the MIMIC III database are highly filtered and further preprocessing is not required.

The same architecture for the CNN as described in the previous section repeated for this experiment. During the training process, the convolutional layers of the network only detect part of training data that resemble different features. While, the first convolutional layers of network detecting very low-level features, the last layers are more sensitive to complex level features. A fully connected layer at the end of the network takes the high-level features learned in the earlier layers of CNN.

A total of 62500 samples of ECG and PPG signals along with synchronized 250 SBP reading were extracted from MIMIC III waveform dataset for this experiment.

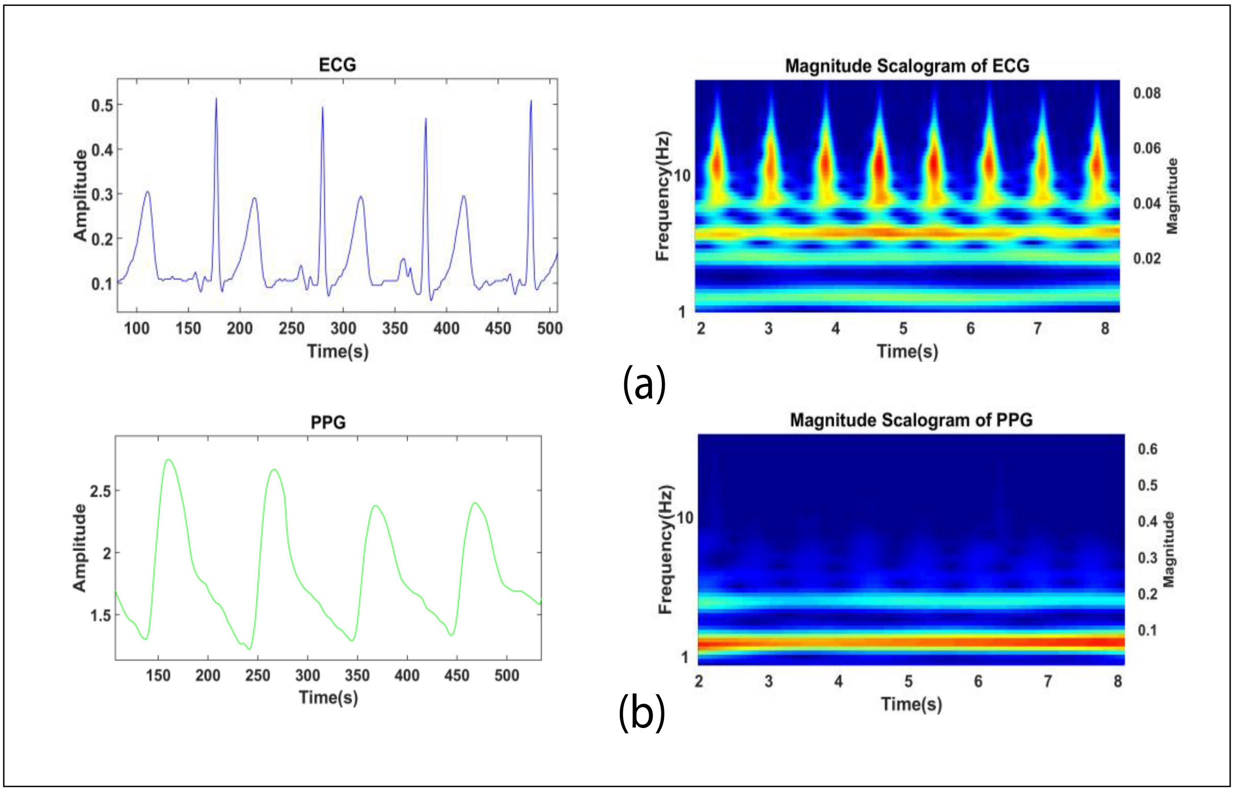

Figure 1: a) A sample of ECG, (b) PPG and their corresponding scalograms.

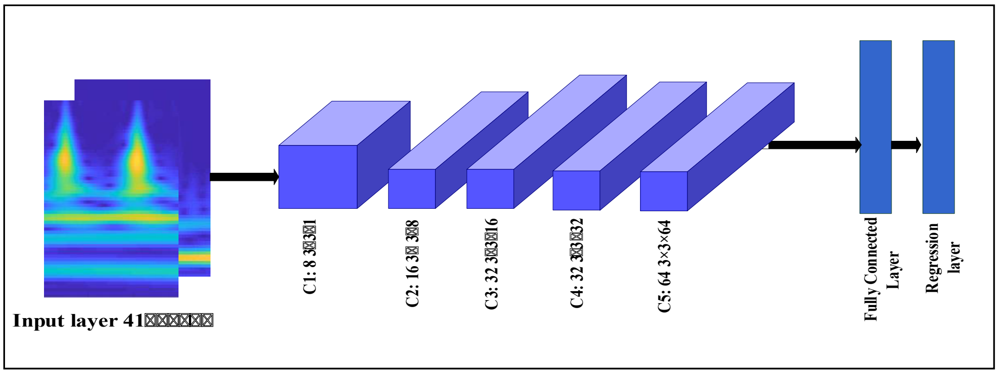

Figure 2: Proposed CNN architectures for SBP estimation using scalogram.

Table 1: Comparison of our modified model with our previous work.

Model	RMSE	Engineered Feature extraction
PTT (Pulse Transit Time) [31]	11	Yes
Pulse wave analysis (PWA) and pulse arrival time (PAT) [32]	10.6	Yes
The first method (previous study)	7.79	No
The second method (previous study)	8.1	No

Table 2: Comparison of the current and previous study results with a different number of samples.

Model	RMSE	Accuracy	Number of samples
First method (this study)	5.43	87.42	500 samples
Second method (this study)	4.82	90.31	62500 samples
First method (previous study) [22]	7.79	82.76	400 samples
Second method (previous study) [22]	8.1	89.66	50000 samples

3. Comparison and Discussion

The experimental results demonstrated a low error rate with high accuracy, confirming that the proposed CNN models are suitable and feasible where the features are not immediately apparent or difficult to extract. Moreover, the preliminary results illustrated an increase in the performance if we employ raw signals for training data compared to using the scalograms of the data.

Also, the experimental results were compared with selected works in the literature. Table 1, summarizes the comparison results of the proposed two methods with two previous works of the authors for SBP estimation. The first column shows the SBP estimation model used and the following column illustrates the error rate, where the last column indicates the use of engineered feature extraction. From Table 1, it is clear that the proposed CNN-based-SBP estimation models showed the least errors in compare to the other methods. The engineered features extraction approach was implemented for the other two studies. Still, we did not employ such a technique as our network learns to extract the related features from ECG and PPG signals intelligently. Accordingly, signal preprocessing and complex engineering feature extraction are not required for the proposed methods, which decrease the complexity and improve the processing time.

Moreover, a comparison between this study and our previous study [22] has been conducted. In the current study, we created a larger database and collected 100 more scalograms images for method one and 12500 more samples for method two. As the complexity of the new approach increased, we added one more convolutional layer to the CNN model to achieve better results. The first 80% of data used for training and the rest used for testing. Table 2, illustrates the results of both methods and shows the number of samples. It confirms that this study, which used a larger database and modified CNN structure, outperforms the previous study.

Moreover, we compared the results with one of the latest study [30], which employed extensive signal processing and feature engineering. The authors extracted a total of 39 features from time domain and six features from frequency, then normalized the features before training their models. They employed three types of machine learning methods to estimate the BP and calculated the RMSE for SBP. It is reported that the RMSE of 5.86 mmHg, 9.50 mmHg, and 10.30 mmHg were calculated for the random forest, support vector machine, and k-nearest neighbors respectively. Compared to the RMSE of 5.43 mmHg obtained for our first method, and 4.82 for the second method, we have achieved better results with less error.

4. Conclusions

In this paper, we investigated the ability of CNN for continuous SBP monitoring and compared its performance with other classical methods. This study presented two deep learning estimation methods using the scalogram of signals and raw signals. It is important to remark that the proposed methods eliminate the engineered or manual feature extraction step and has low computational complexity and faster training time.

The proposed methods can be employed in wearable and smart devices and integrated with cloud computing technology. The wearable devices could collect signals and information, then the cloud platforms can process the data using embedded CNN models. So, it can play a major role in continuous Blood Pressure monitoring and early diagnosis of hypertension, leading to a decrease in the rate of morbidity and mortality associated with hypertension diseases.

Although the proposed method showed promising results and outstanding potential in BP monitoring, there is still room to improve the accuracy and performance of this study. Even though we increased the training data, a larger database will be beneficial for such models. Further validation and optimization with clinical databases will be considered for future work.

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